

Using R to Explore and Visualize Initial Data

Spark is a heavy-duty tool. Let's begin with some lightweight analyses to highlight where to dig in.

Note that this leverages the analyses prepped by the WaPo team here: <https://wpinvestigative.github.io/arcos/index.html>
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```
In [26]: #prepare the libraries:
library(arcos)
library(knitr)
library(tigris)
library(viridis)
library(tidyverse)
library(scales)
library(plyr)
library(dplyr)
```

Pills by County, by Year

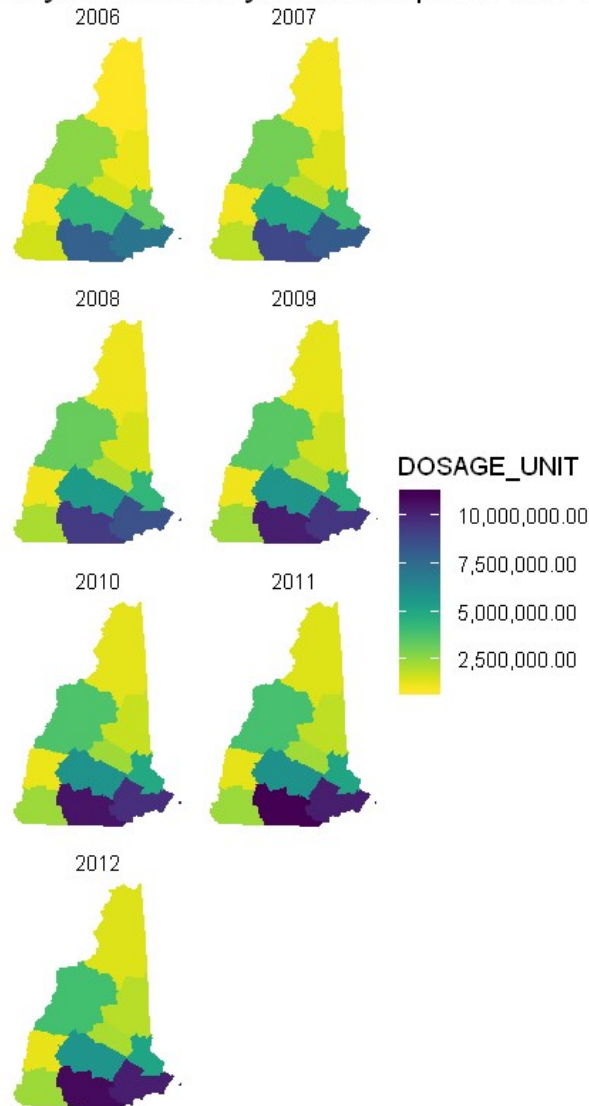
In this section, we will fire up the ARCOS API to begin our search and highlight interest areas:

```
In [27]: #using the arcoss API to get summarized county data:
nh <- summarized_county_annual(state="NH", key="WaPo")
kable(head(nh))
## Set the option for shapefiles to load with sf
options(tigris_class = "sf")
## Function to download county shapefiles in New Hampshire
nh_shape <- counties(state="NH", cb=T)
## Join the county dosage data we pulled
nh<- left_join(nh, nh_shape, by=c("countyfips"="GEOID"))

# Mapping with ggplot2, sf, and viridis
nh %>%
  ggplot(aes(geometry=geometry, fill = DOSAGE_UNIT, color = DOSAGE_UNIT)) +
  facet_wrap(~year, ncol=2) +
  geom_sf() +
  coord_sf(crs = 26915) +
  scale_fill_viridis(direction=-1, label = comma) +
  scale_color_viridis(direction=-1, label = comma) +
  theme_void() +
  theme(panel.grid.major = element_line(colour = 'transparent')) +
  labs(title="Oxycodone and hydrocodone pills in New Hampshire", caption="Source: The Washington Post, ARCOS")
```

BUYER_COUNTY	BUYER_STATE	year	count	DOSAGE_UNIT	countyfips
BELKNAP	NH	2006	4095	1542020	33001
BELKNAP	NH	2007	4916	1943260	33001
BELKNAP	NH	2008	5025	2108300	33001
BELKNAP	NH	2009	5193	2175540	33001
BELKNAP	NH	2010	5647	2302260	33001
BELKNAP	NH	2011	5447	2266640	33001

Oxycodone and hydrocodone pills in New Hampshire



Source: The Washington Post, ARCOS

Initial Takeaways:

It looks like the most pills are distributed in Southern NH. However, we suspect it's also the most populous part of NH, and may or may not be indicative of diversion of prescription meds to the black market.

Clearly, more pills have been distributed over time, seemingly in every county.

Next, let's try to normalize this by population:

Pills Per Capita by County

Normalized for Population:

```

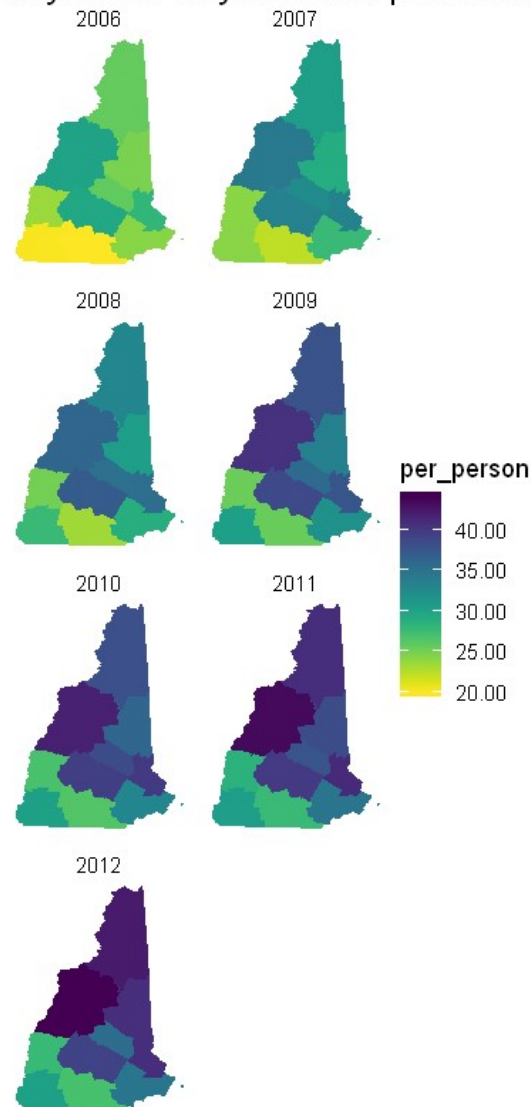
In [49]: #pull in population data from WaPo's helpful API
population <- county_population(state="NH", key="WaPo") %>%
  # isolate the columns so it doesn't conflict in a join (there are doubles, that's
  why)
  select(countyfips, year, population)

left_join(nh, population) %>%
  mutate(per_person=DOSAGE_UNIT/population) %>%
  ggplot(aes(geometry=geometry, fill = per_person, color = per_person)) +
  facet_wrap(~year, ncol=2) +
  geom_sf() +
  coord_sf(crs = 26915) +
  scale_fill_viridis(direction=-1, label = comma) +
  scale_color_viridis(direction=-1, label = comma) +
  theme_void() +
  theme(panel.grid.major = element_line(colour = 'transparent')) +
  labs(title="Oxycodone & hydrocodone pills in New Hampshire per person", caption="
Source: The Washington Post, ARCOS")

```

Joining, by = c("year", "countyfips", "population")

Oxycodone & hydrocodone pills in New Hampshire per person



Source: The Washington Post, ARCOS

Takeaways:

This seems to tell another story! It looks like the northern, more rural counties, experienced a much greater per-capita change over time.

Calculate change in pills per person over time:

Which county had the greatest change in pills per capita in this period?

```
In [29]: #let's bring in population more permanently
nh <- left_join(nh, population)

#calculate pills per person
nh$pills_per = nh$DOSAGE_UNIT/nh$population

ddply(nh, .(BUYER_COUNTY), summarise, mean=mean(pills_per), min=min(pills_per), max=max(pills_per), maxdiff = max(pills_per)-min(pills_per))

Joining, by = c("year", "countyfips")
```

BUYER_COUNTY	mean	min	max	maxdiff
BELKNAP	34.27657	25.65544	38.28040	12.624967
CARROLL	33.21827	24.62011	40.70308	16.082979
CHESHIRE	27.55435	20.03657	30.47373	10.437162
COOS	35.36408	25.51902	42.17571	16.656696
GRAFTON	38.49998	29.98372	43.88256	13.898842
HILLSBOROUGH	24.47257	19.86496	27.54544	7.680484
MERRIMACK	36.65994	29.47486	39.73759	10.262727
ROCKINGHAM	30.59175	24.09055	34.60476	10.514206
STRAFFORD	36.51739	28.06228	41.10330	13.041019
SULLIVAN	25.76191	23.40308	28.39548	4.992404

Conclusion: Rural Counties experienced most volume per capita change overall.

As we can see, the initial images were **misleading**! Coos and Carroll counties experienced the most per capita change in this 7 year period, **not** the counties nearest Boston/Massachusetts.

Next, we use WaPo's API to find which pharmacies were responsible for the greatest per capita pill distribution.

Identify potential "Problem Pharmacies"

The intent here is to identify which pharmacies deserve a closer look into their practices, since high per capita pill concentrations **could be an indicator of diversion to black market**.

```
In [34]: #adapted from here:
#https://wpinvestigative.github.io/arcos/articles/per-capita-pharmacies.html

packages <- c("tidyverse", "jsonlite", "knitr", "geofacet", "scales", "data.table",
"vroom", "formattable")
if (length(setdiff(packages, rownames(installed.packages()))) > 0)
  {install.packages(setdiff(packages, rownames(installed.packages())), repos = "http://cran.us.r-project.org")}

library(tidyverse)
library(lubridate)
library(data.table)
library(formattable)
library(vroom)
library(stringr)
library(scales)
library(knitr)
```

```
In [52]: new_hampshire <- total_pharmacies_state(state="NH", key="WaPo")

# kable(head(new_hampshire))
#need to rerun this, different agg:
population <- county_population(state="NH", key="WaPo")

#had to rewrite this bit:
population <- population %>%
  group_by(BUYER_COUNTY, BUYER_STATE, countyfips) %>%
  summarise_at(vars(population), funs(mean(., na.rm=TRUE)))

population <- rename(population, replace = c("BUYER_COUNTY"="buyer_county"))
population <- rename(population, replace = c("BUYER_STATE"="buyer_state"))
population <- rename(population, replace = c("population"="average_population"))

## Join the data
nh_joined <- left_join(new_hampshire, population)
#> Joining, by = c("buyer_state", "buyer_county")

#want to get pills per person per year:
nh_joined <- nh_joined %>%
  mutate(per_person=total_dosage_unit/average_population/7)

# kable(head(nh_joined))
## Get a list of addresses because it includes BUYER_BUS_ACT information
pharmacy_list <- buyer_addresses(state="NH", key="WaPo")

# We just want the BUYER_BUS_ACT to tell if these are practitioners are retail pharmacies
# This will help us filter out the appropriate pharmacies

pharmacy_list <- pharmacy_list %>%
  select(buyer_dea_no=BUYER_DEA_NO, BUYER_BUS_ACT)

# Join to the original data set
nh_joined <- left_join(nh_joined, pharmacy_list)
# Filter the data so we only have retail and chain pharmacies
nh_joined <- nh_joined %>%
  filter(BUYER_BUS_ACT=="RETAIL PHARMACY" | BUYER_BUS_ACT=="CHAIN PHARMACY")

# Just in case, let's get the BUYER_DEA_NO of pharmacies that aren't really pharmacies
not_pharms <- not_pharmacies(key="WaPo") %>% pull(BUYER_DEA_NO)

#
#what we omit <- nh_joined %>%
# filter(buyer_dea_no %in% not_pharms)

#kable(head(what_we_omit))

# Filter those out, too, if they're in there
nh_joined <- nh_joined %>%
  filter(!buyer_dea_no %in% not_pharms)

# clean up column names so we can make a pretty table
nh_joined <- nh_joined %>%
  select(Pharmacy=buyer_name, City=buyer_city, County=buyer_county, `County population`=average_population,
    Pills=total_dosage_unit, `Pills per person`=per_person) %>%
  mutate(`County population`=round(`County population`),
    `Pills per person`=round(`Pills per person`, 1)) %>%
  arrange(desc(`Pills per person`)) %>%
  slice(1:100)
```


In [53]: `# nil`

Pharmacy	City	County	County population	Pills	Pills per person
RITE AID OF NEW HAMPSHIRE, INC.	COLEBROOK	COOS	33259	2383380	10.2
RITE AID OF NEW HAMPSHIRE, INC.	LANCASTER	COOS	33259	2356640	10.1
CVS MANCHESTER NH, L.L.C.	KEENE	CHESHIRE	77414	3637300	6.7
WAL-MART PHARMACY 10-2634	GORHAM	COOS	33259	1555000	6.7
DARTMOUTH-HITCHCOCK PHARMACY	LEBANON	GRAFTON	87915	4035460	6.6
HANNAFORD BROS. CO., LLC	OSSIPEE	CARROLL	47743	2167420	6.5
WALGREEN EASTERN CO., INC.	ROCHESTER	STRAFFORD	122075	4951350	5.8
MAXI DRUG NORTH, INC.	CLAREMONT	SULLIVAN	43464	1622480	5.3
WAL-MART PHARMACY 10-1975	CLAREMONT	SULLIVAN	43464	1503860	4.9
MAXI DRUG NORTH, INC.	LACONIA	BELKNAP	60296	1986160	4.7
WALGREEN EASTERN CO., INC.	KEENE	CHESHIRE	77414	2382950	4.4
RITE AID OF NEW HAMPSHIRE, INC.	NEWPORT	SULLIVAN	43464	1332000	4.4

Conclusion: These pharmacies have high pill counts relative to their local populations.

This could be a jumping-off point for further investigation.

Note - we did a lot of work to omit non-pharmacies (e.g., hospital pharmacies, which might obviously have relatively high pain medication dispensing). But as we can see, Dartmouth-Hitchcock, a large university hospital in a rural setting, still made it on our list.

The fact that htere are several pharmacies ahead of it on this "hit-list" should raise eyebrows.

In []: `# library("IRdisplay")
display_png(file="Rplot01.png")`